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Deep Learning–Based Change Detection of the Miankaleh Wetland and Development of an Iranian Wetland Time Series Dataset

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ABSTRACT:

The protection of wetlands is a critical concern in environmental science, as these ecosystems serve as vital habitats for a wide range of valuable species. Remote sensing technologies, particularly satellite imagery, provide practical means for continuous monitoring of wetland conditions, including water level and spatial changes. In this study, a nationwide wetland dataset for Iran was generated using Sentinel-2 imagery and image fusion techniques, achieving a spatial resolution of 10 meters. This dataset was designed to support the training and validation of a deep learning model across various seasons and geographical regions. The proposed deep network is characterized by high depth and a reduced number of trainable hyperparameters to enhance computational efficiency while maintaining robust feature extraction. The model was applied to the Miankaleh Wetland, located in Iran's Mazandaran Province, for three consecutive years. Validation against ground truth data demonstrated high performance, with an average overall accuracy of 98%, a Kappa coefficient of 94%, and an F1-score of 99%. Finally, the temporal changes in water area over the three-year period were quantified, fulfilling the main objective of this research.

1. INTRODUCTION

Wetlands are among the most diverse and productive ecosystems on Earth, offering a range of essential services such as groundwater recharge, flood regulation, biodiversity support, carbon sequestration, oxygen production, and climate change mitigation (Liu, Zhang et al. 2022). However, these ecosystems are increasingly threatened by various anthropogenic and environmental disturbances, including industrial pollution, urban encroachment, and climate-induced variability such as altered precipitation patterns and ecosystem shifts (Pan, Lin et al. 2023). These stressors destabilize wetland environments and increase their vulnerability in the face of ongoing climate change. To mitigate the degradation and potential loss of these valuable landscapes, continuous and efficient monitoring is essential. Nevertheless, persistent field-based investigations are often impractical due to their high cost and time requirements. In response, remote sensing technologies have emerged as effective tools for overcoming these limitations and enhancing environmental monitoring and management efforts.

Remote sensing change detection (CD) is the process of identifying the object or phenomenon difference by multi-temporal images over the same geographical area. CD is a very popular and important topic in the field of remote sensing, and it plays a key role in practical applications such as disaster assessment, resource surveys and urban planning (Li, Du et al. 2021).

During the last few decades, many CD methods have been proposed (Chen and Shi 2020). Most early approaches to change detection (CD) in remote sensing relied on handcrafted features and traditional supervised classification algorithms. With the rapid advancement of deep learning techniques—particularly convolutional neural networks (CNNs), which are capable of learning hierarchical feature representations—there has been a significant shift toward data-driven methods. Deep learning has been extensively applied in both computer vision and remote sensing, demonstrating superior performance in various CD tasks (Chen and Shi 2020). Deep learning (DL) has gained substantial attention over the past decade due to its powerful ability to automatically learn complex data representations. DL models are composed of multiple processing layers, each capable of capturing increasingly abstract features from raw input data. This hierarchical learning structure enables the extraction of high-level semantic information, which has proven especially effective in tasks such as image classification, object detection, and change detection in remote sensing (Khelifi and Mignotte 2020).

In recent years, numerous studies have utilized satellite imagery to monitor, model, and analyze the factors influencing surface ecological conditions and their spatiotemporal dynamics. These studies have contributed significantly to understanding environmental changes and patterns across diverse ecosystems.

A considerable number of review articles have been published on the application of remote sensing in wetland studies. These reviews emphasize significant advancements in utilizing remote sensing data for wetland inventory and characterization across diverse climatic zones (Gxokwe, Dube and Mazvimavi 2020). Despite significant advances in remote sensing (RS) technologies, wetland classification remains a challenging task from the RS perspective. A primary challenge in wetland classification arises from the fact that, although each wetland class possesses several distinctive features, they also share ecological similarities both among themselves and with non-wetland classes. Therefore, different wetland types often exhibit similar spectral signatures and/or backscattering characteristics in remote sensing imagery.

In addition, wetlands exhibit significant spatial and temporal variability. Despite these challenges, remote sensing (RS) methods remain the preferred approach, particularly because fieldwork, as an alternative, is labor-intensive, costly, and time-

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consuming. Consequently, numerous studies have focused on developing innovative and efficient RS techniques for wetland mapping with minimal reliance on in situ measurements.
In 2018, Rezaee et al. proposed a CNN-based framework for wetland mapping using optical remote sensing data. Due to limited training samples, they fine-tuned a pre-trained AlexNet model on RapidEye images. Their CNN outperformed the Random Forest classifier, achieving 94.82% overall accuracy—about 16% higher—and improved wetland class accuracy by approximately 30% (Rezaee, Mahdianpari et al. 2018). Pouliot et al. investigated the improvement of Landsat wetland classification using deep learning CNNs, evaluated with two different training/testing datasets. Their results demonstrated consistent performance gains with CNNs, though dependent on object size and scale. To address this, they developed a multi-scale CNN ensemble. When trained on one region and tested on another (spatial extension), the model achieved 62–68% overall accuracy for the Canada Wetland Classification System (CWCS), outperforming a spatial random forest approach. Training with photo-plot samples across the entire region increased accuracy to 69%, with improvements across all classes. Although deep learning offers a promising framework for enhancing wetland classification from remote sensing data, further research is required to boost accuracy for detailed Landsat-based mapping (Pouliot, Latifovic et al. 2019). In 2021, Günen developed a 1D CNN model using the EuroSAT dataset to extract water areas from five different wetlands in Turkey. The proposed deep learning approach was quantitatively and qualitatively compared with traditional machine learning methods, including SVM, LDA, KNN, Canonical Correlation Forests, and AdaBoost.M1. Evaluation was based on metrics such as accuracy, recall, precision, specificity, F-score, and image quality indicators, demonstrating the effectiveness of the 1D CNN (Günen 2021). Pan et al. utilized GF-1 and GF-6 satellite imagery from China's GaoFen series to detect land cover changes—specifically, the conversion of cultivated land to wetlands—in the Sanjiang National Nature Reserve using the STANet model. Their results showed that the BAM-enhanced STANet, combined with ReliefF-based feature selection, achieved F1-Score and mIoU values of 71.72% and 76.92%, respectively—surpassing other models such as UNet, FPN, and PAN. The optimal feature set included Blue, Red, and NIR bands from GF-1, and Red, NIR, and Red Edge 1 from GF-6, indicating their suitability for wetland change detection (Pan, Xu et al. 2022).

One of the key challenges in deep learning applications for remote sensing is the requirement for large volumes of high-quality labeled data, which are often unavailable or limited. As a result, many studies rely on transfer learning techniques, which—while helpful—can sometimes compromise the final model's accuracy. To address this issue, the present study emphasizes the construction of a dedicated, high-resolution wetland dataset as a foundational step toward reducing data dependency and enhancing model performance.

The main objectives of this research are as follows:

1. **Dataset preparation**: To develop a comprehensive wetland dataset covering various regions of Iran across different seasons, considering the high variability in wetland appearance due to seasonal vegetation dynamics and the presence of impurities in water bodies.

2. **Spatial resolution enhancement**: Sentinel-2 data consist of spectral bands with varying spatial resolutions (10 to 60 meters). In this study, appropriate image fusion techniques are employed to downscale all bands to a uniform 10-meter resolution, enabling finer feature extraction and consistency across inputs.

3. **Deep learning network design**: To develop a deep neural network architecture capable of fusing multi-source inputs and extracting optimal spatial-temporal features for time-series classification, specifically tailored for wetland change detection.

4. **Time series analysis**: To evaluate and monitor the annual changes in the Miankaleh wetland in northern Iran over a multi-year period, using the developed model and dataset, with the aim of demonstrating the practical value of the proposed framework in a real-world case study.

2. MATERIAL AND METHOD

In this section, the dataset and the proposed methodology are presented. Accordingly, the section is organized into several subsections, including a description of the study area, data preparation and an overview of the proposed algorithm. The overall workflow of the research methodology is illustrated in Figure 1.

2.1 Study Area

The study area for this research is the Miankaleh Wetland, located in Mazandaran Province, northern Iran. In recent years, this wetland has experienced a severe drought crisis, leading to a significant reduction in its water coverage. Miankaleh is recognized as one of the most ecologically diverse wetlands in West Asia, and possibly globally. It serves as a critical habitat for a variety of endemic Caspian bird and reptile species, and is also an internationally important refuge for migratory birds. The wetland extends approximately 48 kilometers in length and varies in width from 1.3 to 3.2 kilometers. An overview of the study area is provided in Figure 2.

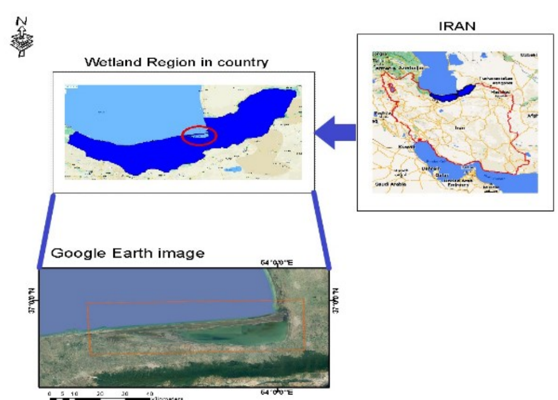


Figure 1. Study area (Dodangeh and Shah-Hosseini 2023).

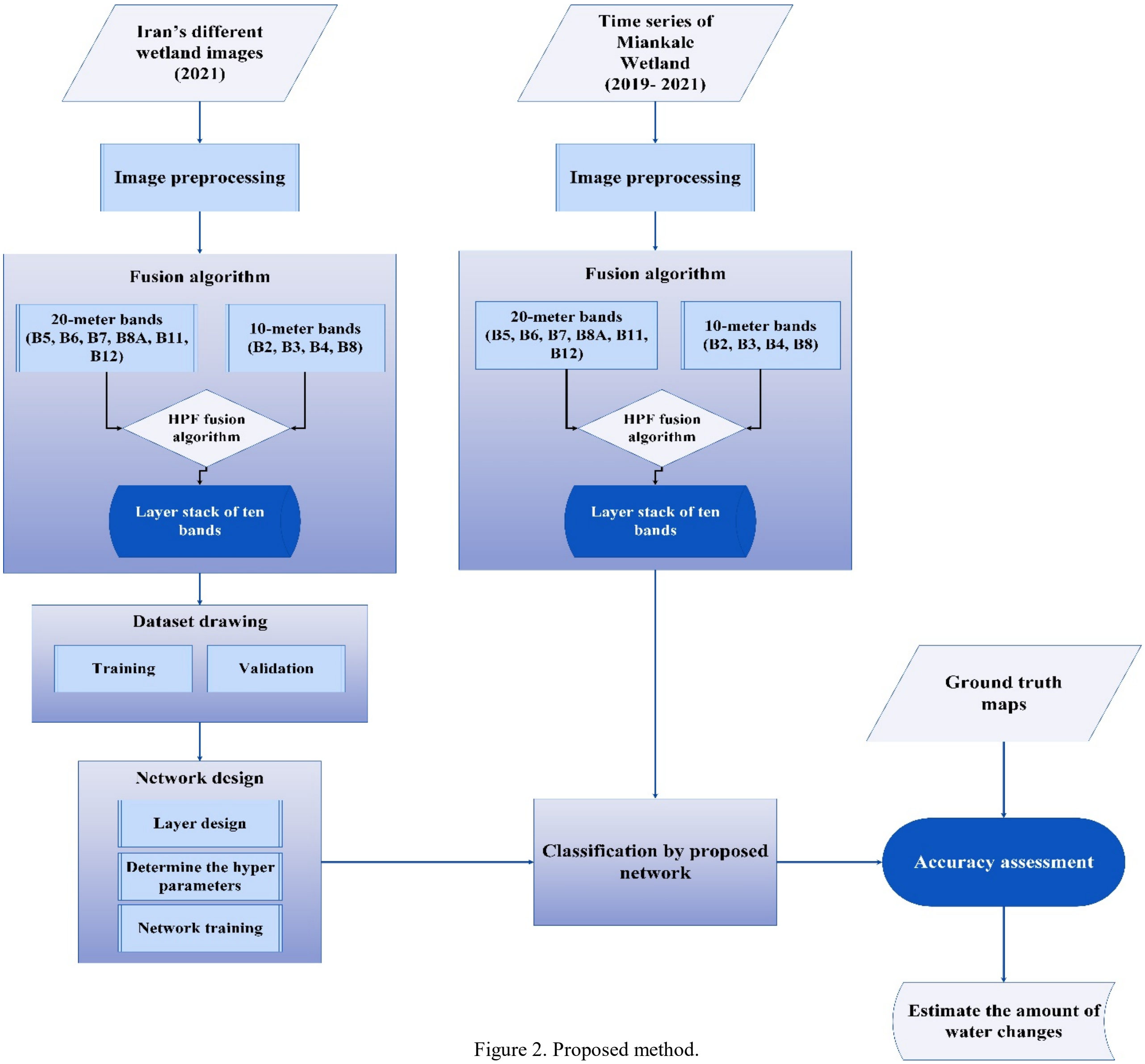


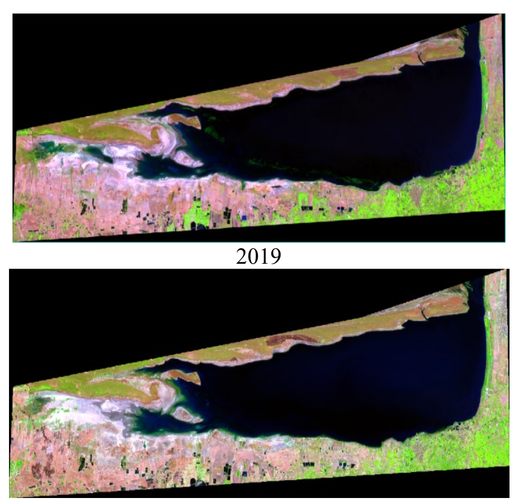
Figure 2. Proposed method.

Given the importance of monitoring the water extent of this wetland, a time series dataset was prepared for a specific season over consecutive years. This dataset serves as the basis for conducting classification and change detection analyses. The overall data preparation process is illustrated in Table 1.

Time	Date	Satellite image
Time 1	2019-08-23	S2B-MSI2A
Time 2	2020-09-06	S2B-MSI2A
Time 3	2021-08-22	S2B-MSI2A

Table 1. Data used for change detection.

The spatial coverage of the satellite images used for the study area is illustrated in Figure 3.



2021

Figure 3. Data used for change detection.

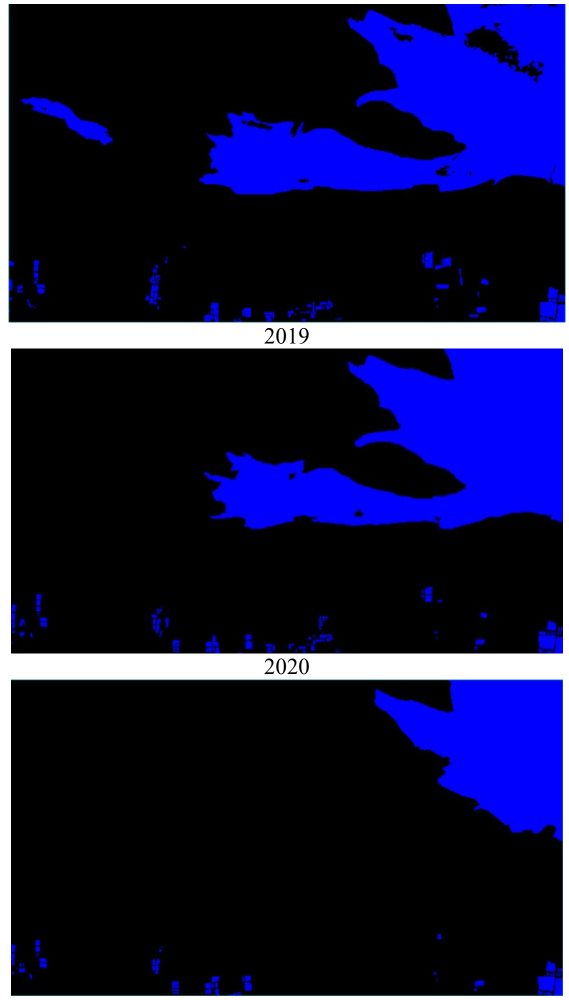
2.2 Dataset Preparation

The dataset used in this study consists of Sentinel-2 satellite imagery obtained from the https://sentinels.copernicus.eu/. Considering the large data requirements of deep learning networks, Sentinel-2 images of various wetlands across Iran were collected for different seasons. For each wetland, specific months were selected based on regional climatic conditions and the rate of environmental changes. These selections are detailed in Table 2.

Study area	Date	Number of patches for each time	Total patches
Ajigol, Almagol, Alagol	2021-02-13	20	**100**
	2021-04-04	20	
	2021-09-01	20	
	2021-11-10	20	
	2021-12-30	20	
Anzali	2021-03-06	20	**100**
	2021-04-20	20	
	2021-07-04	20	
	2021-09-02	20	
	2021-12-21	20	
Shadegan	2021-01-27	40	**200**
	2021-03-28	40	
	2021-05-27	40	
	2021-09-24	40	
	2021-12-23	40	
Total		**400**	

Table 2. Data used for Dataset prepration.

The Sentinel-2 images used in this study are Level-2A (L2A) products, which are atmospherically corrected and therefore do not require additional preprocessing. To enhance spatial resolution, the 20-meter bands were resampled to 10 meters using the High-Pass Filter (HPF) algorithm, which has demonstrated effective performance in image fusion applications (Du, Zhang et al. 2016, Zheng, Du et al. 2017, Kaplan 2018). The final dataset comprises 400 image patches, each with dimensions of 256 × 256 pixels and 10 spectral bands, as summarized in Table 2. These patches were selected across a variety of land cover classes to ensure feature diversity and enhance the generalizability of the deep learning model to other wetland regions. To validate the classification outputs, ground truth data were required. These reference maps were manually created based on expert interpretation of high-resolution Google Earth imagery. Examples of these ground truth maps are shown in Figure 4.



2019

2020

2021

Figure 4. Ground truth maps.

2.3 Proposed Method

This section presents the methodological approaches employed in the study, including the image fusion technique and the architecture of the proposed deep learning network.

2.3.1 HPF fusion algorithm

HPF is a method based on the multi-resolution analysis (Vivone, Alparone et al. 2014). The general principle of HPF is to extract high frequency information that is related mostly to the spatial information from the PAN image by using a high pass filter (Chavez, Sides and Anderson 1991). The high frequency information is then added to each coarse band with a specified weight. Different high pass filters, including the Box filter, Gaussian and Laplacian, can be applied in HPF. This algorithm can be implemented according to the formula below (Palubinskas 2013).

$$MSF = \frac{MSI}{pan*LPF} \quad (1)$$

In the fusion process, **MSF** refers to the fused image, **MSI** represents the original multispectral image, and **LPF** denotes the low-pass filter used in the algorithm. In this study, the High-Pass Filter (HPF) algorithm was applied to fuse six 20-meter bands of Sentinel-2 data to a spatial resolution of 10 meters. Since Sentinel-2 does not include a panchromatic band, a synthetic panchromatic image was generated by averaging the four available 10-meter bands, as suggested in previous studies. Figure 5 illustrates an example of this fusion process implemented in the research.

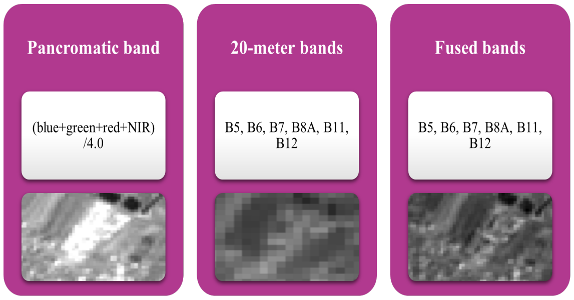


Figure 5. HPF fusion sample.

2.3.2 *Proposed CNN*

Deep learning has emerged as a transformative approach in a wide range of applications, including computer vision, speech recognition, and autonomous systems. One of its key advantages over traditional machine learning methods is its ability to improve performance through increased exposure to data, without explicit feature engineering.

In this study, a deep convolutional neural network is proposed for wetland classification using Sentinel-2 image patches. The architecture is based on an encoder-decoder structure with **multi-branch** design, skip connections, and various optimization techniques to enhance both depth and efficiency. The input to the network consists of image patches of size 256×256 pixels with 10 spectral bands.

The **encoder path** is designed to extract complex spatial and spectral features. Initially, it consists of sequential convolutional layers with 16 and 32 filters respectively, each followed by batch normalization and ReLU activation. A dropout layer with a rate of 0.15 is included to prevent overfitting. Another branch with 8 filters follows a parallel path using max-pooling and dropout, forming the basis for multi-branch feature extraction.

This **multi-branch structure** allows the network to learn feature representations at multiple depths and receptive fields simultaneously. Features from different branches are then combined using **concatenation layers**, which enrich the final representation by integrating information learned at different levels of abstraction.

The **bottleneck section** of the network further processes the extracted features using additional convolutional layers with batch normalization and ReLU, enabling more compact and high-level representation.

The **decoder path** reconstructs the spatial structure of the input by applying transposed convolution (Conv2DTranspose) and further concatenating features from earlier layers. This skip connection strategy ensures the preservation of spatial details that might otherwise be lost during downsampling.

Finally, the network output is passed through a dropout layer (rate = 0.5) and a Softmax activation function to produce a pixel-wise classification map in two classes (wetland and non-wetland).

The proposed architecture benefits from:

- **Multi-branch feature extraction**, enabling more robust learning,
- A limited number of **trainable parameters** (49,674 out of 49,978 total), reducing overfitting risk,
- Use of **batch normalization** and **dropout** to stabilize training and improve generalization.

Figure 6 illustrates the complete architecture of the proposed multi-branch CNN.

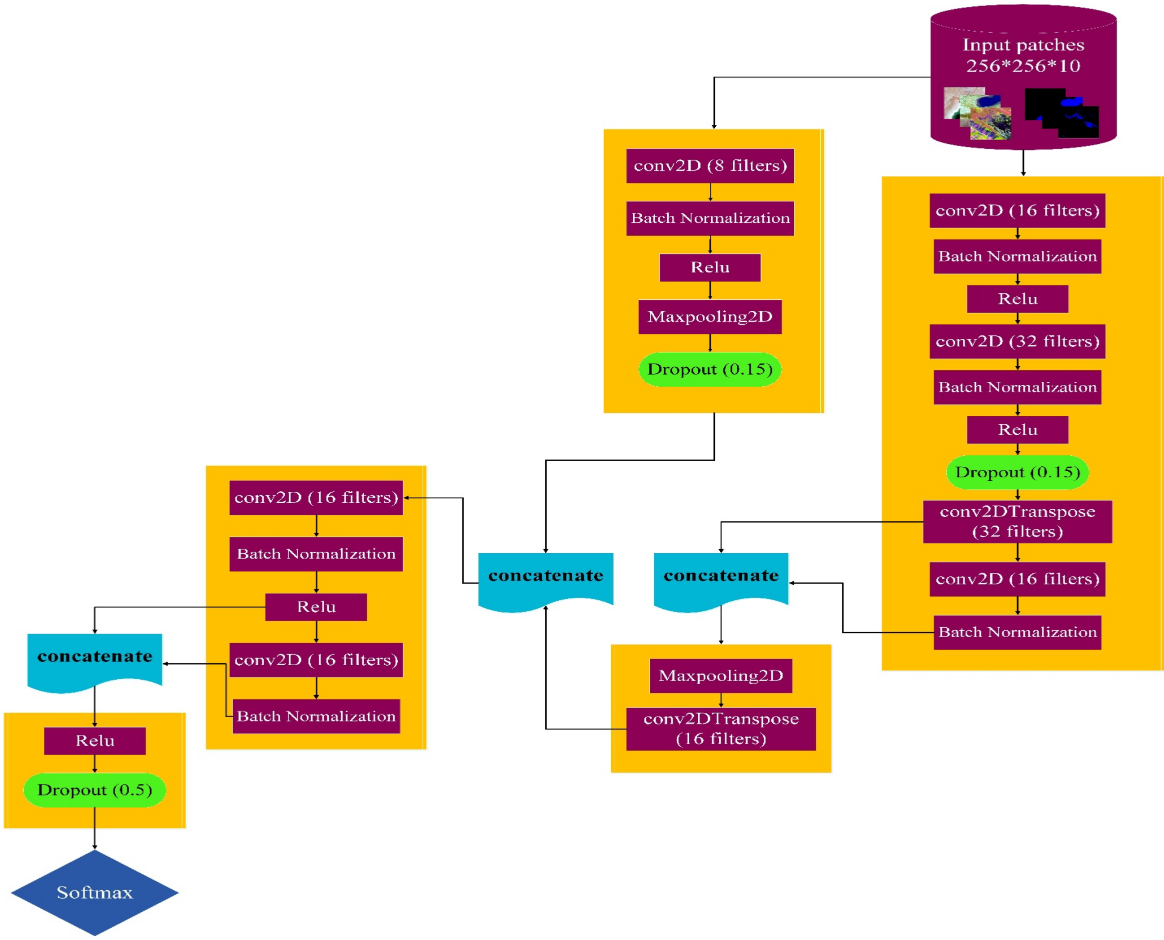


Figure 6. Proposed network architecture.

The proposed network comprises a total of 49,978 parameters, of which 49,674 are trainable and 304 are non-trainable. For model optimization, the Adam optimizer was selected with an initial learning rate of 0.01, based on its proven performance in image classification tasks as reported in previous studies. Multiple learning rates were empirically tested to identify the most effective value for the network. To train the model, the dataset of 10-meter resolution patches was split into 70% for training and 30% for validation. The training process was conducted over five epochs, and the corresponding training and validation results are presented in Figure 7.

Figure 7. Network training result.

The validation accuracy and loss curves demonstrate that the model has undergone effective and reliable training. Furthermore, the close alignment between the training and validation metrics suggests that the model does not suffer from overfitting. Nevertheless, to further evaluate the model's generalization capability, it is essential to apply the trained network to an independent test set, specifically the Sentinel-2 images of the Miankaleh wetland.

3. RESULT

This section is organized into two main parts: generation of classification maps and accuracy assessment.

3.1 Map Generation

After training the network and saving its weights, predictions were performed on the test dataset, which includes Sentinel-2 images from the years 2019, 2020, and 2021. The test images used for classification have dimensions of 1024 × 1792 pixels. Areas of interest—specifically, those corresponding to observed changes in the wetland—were selected such that their dimensions are divisible by 256, allowing for tiling into 256 × 256 patches. Using a Python-based implementation, 28 tiles were generated for each year.

Following classification, the resulting tiles were mosaicked to reconstruct full-scene classification maps. The classification outputs for the three years are illustrated in Figure 8.

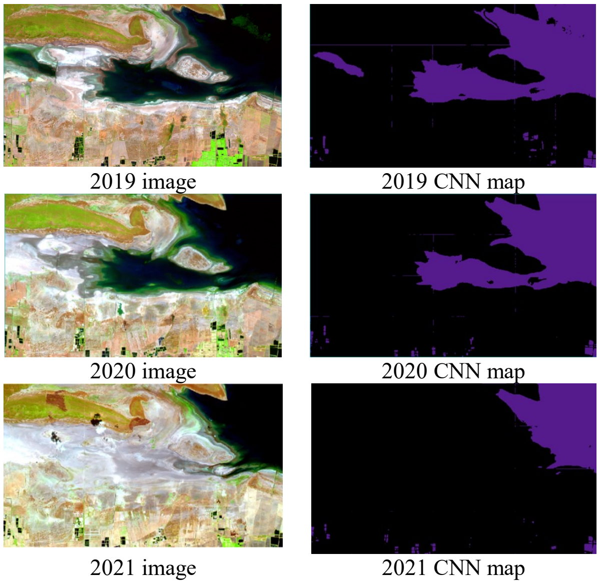


Figure 8. CNN classification results.

The band combination used to display the classification results is SWIR1, NIR, and Red, which enhances the visual interpretation of water and vegetation features. A visual comparison between the classification maps and the original satellite imagery clearly demonstrates the high accuracy of the proposed method in capturing the extent and dynamics of wetland areas.

However, visual assessment alone is not sufficient to validate classification performance. A classification remains incomplete without a quantitative accuracy assessment, which measures how well the classifier has labeled image pixels relative to a ground truth reference (Bharath, Nimish and Chandan 2020). To rigorously evaluate the effectiveness of the proposed approach, an accuracy assessment is carried out in the following section.

3.2 Accuracy Assessment

In this section, the classification results are evaluated using multiple accuracy assessment metrics, based on comparison with the ground truth maps. These widely accepted evaluation criteria provide a comprehensive view of the classification performance.

- Overall Accuracy (OA) indicates the proportion of correctly classified reference sites out of the total number of reference sites. It is expressed as a percentage, where 100% denotes a perfect classification. While OA is straightforward and easy to interpret, it provides only a general indication of classification performance.

- Omission Error (Type I error) occurs when a reference site is excluded from its correct class in the classified map. It reflects instances where the actual land cover type is omitted. This is calculated by examining each class column in the confusion matrix, summing the incorrect classifications, and dividing by the total number of reference samples for that class. High omission errors indicate under-classification.

- Commission Error occurs when a site is incorrectly assigned to a certain class, indicating over-classification. This is calculated by summing the misclassified entries across each class row and dividing by the total number of classified samples for that class.

- Producer's Accuracy measures the probability that a reference sample is correctly classified. It reflects the perspective of the data producer or classifier and is calculated as the number of correctly classified reference samples divided by the total number of reference samples for that class. It is the complement of omission error (Producer's Accuracy = 100% − Omission Error).

- User's Accuracy indicates the likelihood that a class on the map truly represents that category on the ground. It is calculated by dividing the number of correctly classified samples in a class by the total number of samples classified into that class. It is the complement of commission error (User's Accuracy = 100% − Commission Error).

- Kappa Coefficient (κ) is a statistical measure of agreement between the classification and a random assignment. It accounts for the possibility of the agreement occurring by chance. The Kappa value ranges from −1 to 1, where values near 1 indicate strong agreement, 0 represents random agreement, and negative values indicate worse-than-random performance.

- F-score (or F1-score) is a harmonic mean of Precision and Recall. Precision (positive predictive value) is the ratio of true positives to all predicted positives, while Recall (sensitivity) is the ratio of true positives to all actual positives. The F1-score balances these two metrics and is especially useful in imbalanced class distributions.

Map / Criteria	2019	2020	2021
Overall accuracy	**97.41**	**98.58**	**98.88**
Kappa coefficient	**92.87**	**95.87**	**94.55**
F1_score	**98.30**	**99.09**	**99.36**
Producer accuracy	**97.41**	**98.58**	**98.88**
User accuracy	**97.50**	**98.57**	**98.95**
Commission error	**2.49**	**1.43**	**1.05**
Omission error	**2.59**	**1.42**	**1.12**

Table 3. Classified map accuracy assessment.

As previously discussed, the classification results demonstrate high accuracy across all evaluation metrics, highlighting the effectiveness of the developed network in binary classification tasks. Following this, the **water-covered area** was estimated for each image based on the classification outputs. The results of this estimation are presented in the diagram below, providing a clear depiction of the **temporal variation in water extent** across the study period.

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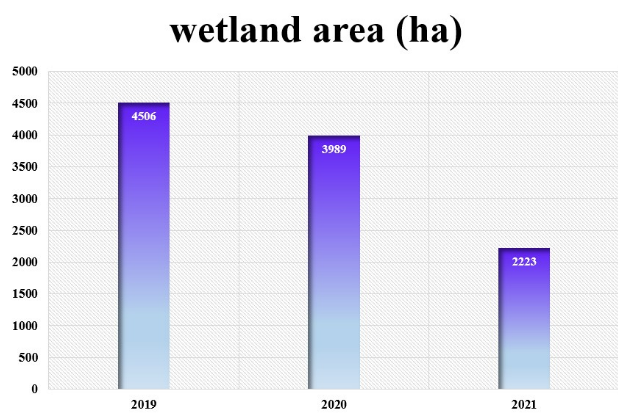

Figure 9. Water area in different years.

Based on the calculations conducted from the classification results, the Miankaleh wetland experienced a **reduction of approximately 2,283 hectares in water-covered area** between 2019 and 2021.

4. DISCUSSION

In this study, a deep learning network based on an autoencoder architecture was developed to effectively extract features and classify time series satellite images for detecting changes in the water areas of Miankaleh wetland. The results demonstrated that the proposed network, with a relatively small number of parameters, was able to produce reliable classification maps with high accuracy. Additionally, comparisons with ground truth data confirmed the validity of the classification outcomes.

Despite the acceptable accuracy achieved, this research faces several key limitations:

1. **Limited Training Data**: One of the main challenges in applying deep learning to remote sensing is the scarcity of accurately labeled training data. In this study, ground truth data were generated from Google Earth images and expert knowledge, which may introduce some bias in evaluation.

2. **Limited Spatial Generalization**: The trained network was primarily developed using data from a few specific wetlands, and extensive evaluation on other geographic areas was not conducted. Therefore, the model's generalizability to different regions remains to be tested.

3. **Limited Temporal Resolution**: The analysis of change trends was conducted over only three consecutive years. This relatively short timeframe may overlook longer-term ecological patterns.

4. **Lack of Complementary Environmental Data**: The proposed model is based solely on spectral data, without integrating other potentially informative environmental variables such as meteorological data, water depth, or vegetation characteristics.

To enhance the model's performance and extend its applicability, the following recommendations are proposed:

1. **Integration of Complementary Data**: Combining spectral data with radar (SAR) and environmental datasets (e.g., weather, soil moisture, temperature) could improve model accuracy and robustness.

2. **Extending the Temporal Scope**: Expanding the study to cover longer time periods (e.g., a decade or more) could help identify more accurate and meaningful long-term ecological trends and climate change impacts.

3. **Development of Multi-class Models**: While this study focused on binary classification (water vs. non-water), designing networks capable of multi-class classification (e.g., distinguishing between reed beds, agricultural land, marshes, etc.) would provide a more comprehensive understanding of wetland ecosystems.

4. **Exploration of Hybrid and Transfer Learning Models**: Utilizing hybrid architectures that incorporate temporal modeling (such as LSTM layers) or fine-tuning pre-trained deep networks may improve performance especially when training data are limited.

5. **Comprehensive Spatial Validation**: Applying and testing the model on other wetlands across different regions in Iran would help evaluate its generalizability and robustness.

5. CONCLUSION

The importance of preserving and maintaining wetlands is globally recognized, as they are among the most vital natural habitats. Due to ongoing temperature increases and decreasing precipitation, drought conditions in these areas are rapidly intensifying. Therefore, continuous monitoring of wetlands is essential. In this study, a 10-meter resolution dataset of Iran's wetlands was prepared using image fusion techniques across different seasons and climatic conditions, reflecting the spectral variability of wetlands caused by their unique vegetation.

The application of image fusion and pan-sharpening methods notably improved the detection accuracy, particularly along water surface boundaries. Furthermore, the satellite images were classified into two classes using a deep learning approach. The proposed network was designed to have considerable depth while maintaining a relatively low number of training hyperparameters. Accuracy assessments over three consecutive years demonstrated the high efficiency and capability of the network to accurately delineate wetland areas despite their inherent complexities.

Future work will focus on expanding the size of the training dataset to further improve model performance. Additionally, some classification errors related to the mosaicking of test tiles were observed, which will be addressed in subsequent research.

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